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Knowledge Spillovers in Strategic Alliances: The Case of Biotechnology

by

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ABSTRACT

This paper explores the extent to which strategic alliances were a conduit for know-how exchange between new biotechnology firms and incumbent partners during the middle years of the biotechnology revolution. It presents empirical evidence of the patenting and patent citation behavior of 238 biotechnology R&D strategic alliances and joint ventures from 1985 - 1991. Contrary to other theoretical and empirical work suggesting that alliances are a strategic device to efficiently appropriate know-how from partners, the evidence provided here suggests that alliance partners in biotechnology have tended to co-specialize into different aspects of R&D projects' vertically related stages.

Keywords: Strategic Alliances, Complementary Capabilities, Radical Innovation, Biotechnology

1 Introduction

One interesting facet of the biotechnology 'revolution' is the extent to which incumbent pharmaceutical and chemical firms have adopted many of the tools of biotechnology. Biotechnology inherently involves high risk and uncertainty in technological feasibility, efficacy, safety, and market acceptance, as well as a relatively long technology development cycle. These characteristics of the technology have caused the innovation trajectory of areas implicated by biotechnology tools to fan out in multiple directions rather than proceeding in an orderly, linear way. As a result, the decision by market incumbents to adopt the new technologies has been very difficult. The paradigm of incumbent displacement during radical innovation oversimplifies and obscures some of the actions of incumbents who may attempt to accept a new technological trajectory in a more targeted way (McKelvey, 1996).[1] Firms may choose to wait, or to selectively adopt technologies through specific alternative organizational forms such as contract, alliance, or acquisition of new firms or new employees. They may also engage in strategies to appropriate new capabilities more broadly, such as funding university research for early access rights to know-how, or liberal policies on personnel external research links. It is clear that pharmaceutical firms have 'learned' and are employing many techniques for large molecule research. One strategy employed by all pharmaceutical firms has been to obtain access to biotechnology capabilities through alliances with dedicated biotechnology firms. But the question remains whether the alliances were used to learn new capabilities rather than to simply access complementary assets through something closer to arms-length dealing. This paper explores the extent to which alliances permitted incumbent firms to absorb new competencies, as well as the extent to which biotechnology firms learned new capabilities from their alliance partners.

[1] For an interesting prediction of the 'beginning of the end' of pharmacogenomics, see Jean-Michel Claverie, "What If There Are Only 30,000 Human Genes?," *Science*, February 16, 2001, Vol. 291(5507), pp. 1255-1257

An implicit or explicit theory repeated in the organization theory literature is that firms can use strategic alliances to learn new know-how and capabilities from their partners. Firms can use alliances to appropriate skills outside the formal agreement, and diffuse the new knowledge throughout other parts of their organization (Hamel, Doz, and Prahalad, 1989; Hamel, 1991). Successful firms, it is argued, use alliances to appropriate new skills rather than simply to out source a stage of product development. Strategic alliances might be a particularly efficient method of learning new skills, as they could enable the transfer of tacit knowledge that would be difficult or more costly to convey through alternative means such as arms-length contracting.

It is important to recognize, however, that firms participating in strategic alliances desire to limit the ability of their partners to appropriate knowledge assets (Kale, Singh, and Perlmutter, 2000). This can be achieved by designing an alliance mechanism that limits personnel exchange, delineates broad rights over intellectual property, and structures 'joint R&D' as a serial (vertical) chain of research that minimizes overlaps and restrains interaction between partners. Through various contractual mechanisms that put bounds on how the research or development process is conducted, firms can reduce the prospect of knowledge spillover (Majewski and Williamson, 2002). Perhaps this is why in both case studies and empirical approaches, 'learning' across alliance partners does not occur in every alliance (Hamel, Doz and Prahalad, 1989; Mowery, Oxley and Silverman, 1996).

Alternatively, firms may form alliances primarily to access complementary capabilities of partners and only tangentially, if at all, to learn from them (Teece, 1992; Pisano, Shan, and Teece, 1988). For example, alliances can combine complementary skills in R&D with those in production, marketing or distribution. Even in these cases, however, know-how can be context specific, and therefore firms would prefer to ally rather than to use arms-length contracts susceptible to hold-up (Williamson, 1996). Comple-

mentary assets can be context specific while simultaneously experiencing economies of scale in their generally applicable components, implying efficiencies to alliance above those of vertical integration. Alliances can be an efficient organizational mode in integrating know-how while preserving efficiencies of specialization (Grant and Baden-Fuller, 1995). For example, they may permit access to technological complementarities in ways that can lower development lead time relative to market transactions (Hagedoorn and Schakenraad, 1990).

There are several industry-specific hypotheses that may explain firm participation in alliances. The biotechnology and pharmaceutical industries are two of the most active industries in strategic alliances (Hagedoorn, 2002; Hagedoorn, 1993; Harrigan, 1985). These industries also are very innovative, having high R&D intensities and high patent propensities relative to other industries. Yet, are they involved in strategic alliances specifically to absorb new R&D-related (science-based) knowledge? Many biotechnology-pharmaceutical alliances are formed for the purposes of manufacturing, marketing, or distribution, where the pharmaceutical firms have substantial assets in these areas, and biotechnology firms typically do not (particularly over the early period of the industry). Even within R&D alliances, the typical biotechnology-pharmaceutical pairing will involve contract-based research. Here, the pharmaceutical firm will fund its biotechnology partner to conduct R&D, and will retain the rights to the outcome of this research. As opposed to the notion of joint learning, one hypothesis is that in biotechnology, strategic alliances exhibit *one-way* flows of knowledge, from biotechnology firm to its funding partner. Another hypothesis is that even at the R&D level, alliance partners bring complementary skills into the alliance, specialize in their core competencies, and fail to use the alliance for knowledge exchange.

To date, few empirical studies have attempted to explore the extent

to which alliances are used for know-how exchange or co-specialization.[2] Cross-industry evidence suggests that most firms learn from their alliance partners (Mowery, Oxley, and Silverman, 1996, 1998). Yet evidence from biotechnology is mixed. Zucker and Darby (1997) find that attracting and retaining new employees was a primary driver of pharmaceutical adoption of biotechnology, while alliances were used for access to complementary skills deemed to be lower priority. In contrast, Rothaermel (2001) finds a correlation between biopharma alliances and incumbent pharmaceutical new product development.

This paper examines the nature and direction of information exchange in biotechnology strategic alliances. Did partner firms both learn from each other? Did they co-specialize? Or did they organize a one-way transfer of know-how? To explores these questions the paper compares the characteristics of issued patents pre- and post-alliance for a sample of 238 biotechnology R&D strategic alliances and joint ventures that were formed between 1985-1991 by 91 biotechnology firms and their partners implicating 134,654 patents and 929,613 patent citations. In contrast to the empirical evidence of previous studies using patent citation data in a multi-industry panel that firms learned from their partners in most alliances (Mowery, Oxley, and Silverman, 1996, 1998), this paper suggests that alliances in biopharmaceuticals during the 1985-1991 time frame were not a primary conduit of know-how exchange. I fail to find evidence consistent with the hypothesis of knowledge flow across alliances. Neither patent cross-citation rates, nor technology overlap measures based on patent fields support the hypothesis of knowledge flow. The results of this paper are consistent with alternative theories, particularly that firms in alliances provide *complementary* skills and that post-alliance, they do *not* move into each other's fields of expertise.

Section 2 describes empirical findings and trends in the industry. Section 3 discusses the hypotheses and research design, and points to limitations of

[2]For a recent survey of the alliance literature, see Hagedoorn, Link, and Vonortas, 2000.

patent-based measures. Section 4 describes the data. Section 5 details the results, and 6 concludes.

2 Evidence and Industry Trends

The question of whether firms engaged in joint R&D are more productive or more innovative has been the subject of a large body of literature. It has gained more attention in recent years, as researchers have noted the increased incidence of strategic alliances (Hagadoorn, 2002; Hagedoorn, Link and Vonortas, 2000). Biotechnology and pharmaceuticals have been two intertwined industries most active in forming alliances (Hagedoorn, 1993, 2002). Yet the evidence that pharmaceutical success in gaining biotechnology capabilities through alliances is mixed (Zucker and Darby, 1997; Rothaermel, 2001), and the trend toward alliances has been concurrent with declines in overall research productivity in the ethical pharmaceutical industry (Henderson and Cockburn, 1996). Evidence suggests that firms with more liberal policies on knowledge exchange are more successful in these industries. Successful firms tend to have greater ties to the university communities (Zucker and Darby, 1996). They also tend to have liberal coauthorship policies, permitting internal scientists to publish papers with scientists external to the firm (Cockburn and Henderson, 1998).

The role of strategic alliances in inter-firm knowledge transfer has received little direct empirical attention. Mowery, Oxley, and Silverman explore the role of alliances in knowledge transfer using patent citations. Using inter-industry data, they find that some alliances result in technological convergence - partners cite each other more post alliance, and others result in divergence - partners cite each other less post alliance (Mowery, Oxley, and Silverman, 1996). Their results also indicate that allying firms are more likely to have a common technological base than non-allying firms (Mowery,

Oxley, and Silverman, 1998).

The Mowery, Oxley, and Silverman evidence is consistent on average with the Resource-based hypothesis that firms engage in alliances to appropriate knowledge assets from their partners. However, some alliance partners diverge in technology space. One interpretation is that divergence implies 'failure' by the alliance partners to use the alliance to learn. An alternative interpretation, however, is that the alliance was designed for firms to specialize in core competencies and designed to prevent partners from appropriating each others' core assets. A question that is not explored is whether partners absorb knowledge assets at different rates. One hypothesis is that firms with greater absorptive capacity are more likely to absorb new knowledge within an alliance. An alternative view is that many alliances are more analogous to contract R&D agreements designed to enable one firm to appropriate the technology of its alliance partner.

That R&D 'alliances' may often be designed in a more arms-length way is particularly appropriate to the experience in the early to middle years of the biotechnology industry. Often, alliances were mechanisms for pharmaceutical firms to fund the R&D projects of biotechnology partners in exchange for rights to resultant technology. These deals were significant sources of revenues for the start-up biotechs. Table 1 shows that the average research or development alliance generated roughly two-thirds the proceeds of the average stock offering. In return for funding out sourced biotech R&D projects, pharmaceutical firms gained rights to the resultant research, and committed to providing complementary skills in marshalling candidate products through regulatory processes, inproducing large scale quantities product in some cases, and in marketing new products widely. This structure enabled pharmaceutical and chemical firms to 'take an option' on new technologies without committing internal resources to learn new capabilities. Consequently, it is possible that many alliances resulted in no skill-transfer, or a one-way skill transfer (from biotech to partner) at best.

There were several primary areas of research embodied in the alliances during the period of this study, 1985-1991. Many alliances covered monoclonal antibody research, involving splicing genes into growing mediums to produce large scale quantities of antibodies. Several others, spanning human pharmaceuticals, vetrinary applications, and agriculture, involved the development of oligonucleotide probes to target genetic sequences. Biotechnological capabilities dramatically accelerated during this period, with advancements made in tools used as essential inputs to R&D. Toward the later end of the period, advances made in polymerase chain reaction (PCR) enabled researchers to radically increase productivity and the pace of discovery (Cook-Deegan, 1996).[3] Several of the drug discovery alliances during the period were contracts for the biotechnology firm to develop probes for specific disease areas for which the pharmaceutical partner already had a drug development program. For pharmaceutical and agrochemical firms, the relationships therefore expanded the scope of technological trajectories to cover the same disease areas or crop technologies without requiring them to fully commit internal resources to learning new capabilities.

The 'revolution' did not only affect pharmaceuticals. Firms in industries such as agriculture (primarily seed and crop pest research), and chemicals (primarily pesticides and fungicides) were allying with biotechs for R&D projects during the period as well. The period was one where many of the large biotechnology partners were exploring R&D paths outside their core areas of expertise. For example, Du Pont was involved in biotechnology alliances regarding probes for agrochemicals, as well as alliances for monoclonal antibody research in human disease. And Shell was involved in alliances regarding bioinsecticides. Moreover firm industry areas were not bright lines. Many conglomerates were engaged in pharmaceutical and chemical R&D during some of the period. The industry picture of which firms constituted pharmaceutical firms evolved, as merger and divestiture activity continued. These conglomerates included firms such as Hoechst,

[3]The Cetus PCR patent is the single most cited patent in the data.

Eastman Kodak (Sterling Drugs), F. Hoffman-La Roche, Rhone Poulenc Rorer, and American Healthcare Products (American Cyanamid). Table 2 shows the diversity of partners to the dedicated biotech firms during the period.

Given the revolution in technology and the evolution in industry structure, the central question is whether alliances enabled incumbents to absorb new capabilities to move into the next technological wave.

3 Hypotheses and Research Design

There are three competing theories regarding the purpose and effect of R&D strategic alliance formation and joint ventures. The first theory is that firms ally for mutual knowledge sharing. If firms ally for mutual knowledge sharing, we should expect to see technology flows in both directions: from biotechnology firms to their partners, and from partners to biotechs.

H1: On average, alliances are designed for knowledge exchange from each firm to its partner. Both firms in the alliance learn from each other.

The second theory that explains why biotechnology firms participate in alliances is that partner firms provide funds for biotechnology R&D for access to the new technology. If this were the case, then we would expect to see technology flows from biotechnology firm to pharmaceutical and chemical partner firms, but not vice versa. In addition, we should also expect to see pharmaceutical firms migrating toward biotechnology fields over time.

H2: Pharmaceutical and chemical companies acquired capabilities from biotechnology firms through their alliances, but biotechnology firms did not use alliances to acquire capabilities from their pharmaceutical and chemical

partners. Most biotechnology strategic alliances were more analogous to contract R&D with one-way knowledge flows.

A third alternative hypothesis is that alliances result in specialization. Each partner brings distinct skills into the agreement and retains focus in their own technological areas of expertise. In this case, we would expect to see little or no substantial technology flows between each firm, and little migration in technology space over time.

H3: Each firm in an alliance maintains core capabilities in biotechnology alliances. Partners specialize. Know-how is not exchanged.

To explore these hypotheses of the role of strategic alliances on knowledge transfer, I use two alternative methodologies. Both methods have limitations. The first method, cross-citations, is the method used in papers by Mowery, Oxley, and Silverman (1996, 1998). As explained below, the cross-citation measure is likely biased toward an incorrect finding of learning in alliances. I attempt to control for the bias. The second measure, proximity, is an illuminating and complementary measure, but provides less direct evidence of firm-learning specific to the alliance.

Perhaps a more important outcome of the study is the illustration of how difficult it is to use patent-based measures for cross-firm learning in in new technological fields. The huge disparity in the sizes of patent portfolios across partners in the early biotech industry may cast some doubt on using patents as a measure of know-how exchange. For example, 67 alliance observations were eliminated from the analysis because the biotechnology firm was awarded no patents during either the period before or after the alliance. This finding is in part because young firms in new technological fields may not have patents pre-alliance. In fact, many use the alliance as a funding vehicle to develop new patentable technologies. The finding is also in part because many firms in start-up industries exit through bankruptcy

or acquisition before the long time frame to patent new technologies.

Despite their limitations, the cross-citation rates and the proximity measures together are useful complementary measures to explore the effects of strategic alliance participation on firm learning in large samples of data. Patenting is a critical strategy for firms to protect their core assets. While learning non-patentable know-how is surely a part of alliances, this paper focuses on R&D alliances where one would expect patents to be an important output. Moreover, because the biotechnology and pharmaceutical industries are among the most active industries in patenting behavior, it is reasonable to expect that learning would be reflected in patents and in patent citations.

3.1 Cross-Citations

The method that prior authors have used to look at technology flows between partners utilizes patent citations (Mowery, Oxley, and Silverman; 1996, 1998). When firms file their patent applications with U.S. Patent and Trademark Office, they are required to cite all prior art upon which their new innovation is based. Firms that fail to include relevant prior art in a patent application risk invalidation of their patent should a competitor successfully establish in litigation that the invention was covered by prior art. Consequently, firms have some incentive to cite relevant prior art. However, using specific citations as indicators of knowledge flows between cited and citing firms can generate false positive results. This is because conservative patent attorneys often add citations to patent applications upon reviewing prior art that were unknown to the inventor. Nonetheless, survey data suggests that citations are a meaningful, albeit noisy, indicator of communication between firms. Citations are correlated with perceived value of invention (Jaffe, Trajtenberg, and Fogarty, 2000a and 2000b). They are also correlated with the market value of the firm (Hall, Jaffe, and Trajtenberg, 2000) and the market value of the individual patent (Harhoff, Narin, Scherer, and Vopel, 1999).

The Mowery, Oxley, and Silverman method of calculating knowledge flows in an alliance looks at the number of citations to a partner patent as a fraction of all the firm's citations. This measure, where c_{ij} is the number of times firm i cites firm j, and N_i is the total number of all patents cited by firm i, is:

$$\text{Cross-citation}_{MOS} = \frac{c_{ij}}{\sum_{j=1}^{N_i} c_{ij}} \tag{1}$$

The variable of interest using this methodology is the change in citation behavior, measured as the difference between pre- and post-alliance cross-citation rates. The paper explores the change in the citation propensity across partner firms, breaking down observations across types of alliance: joint ventures (that could involve more co-ownership of resulting assets), research alliances, and development alliances, and also across types of partners: pharmaceutical, biotech, or non-biopharma.[4]

While the cross-citation rate provides a very direct method of measuring technology flows across firms, it suffers from several weaknesses. First, because pharmaceutical firms have much larger patent portfolios than their biotechnology partners, the odds that a biotechnology patent would cite a pharmaceutical patent are higher than the odds that a pharmaceutical patent might cite a biotechnology patent based on random assignment. As a result, the rate at which firms cite each other may be a poor method for comparing uni-directional knowledge flows for these firms. However, the *change* in cross-citation rates pre- vs. post-alliance should not be biased, assuming similar rates of patenting for both partners pre- and post- alliance. Tables 2 - 3 list the total number of patents in firm portfolios from 1980-1996.

[4]The label 'non-biopharma' is intended to capture the variety of alliance partners that are neither primarily dedicated biotech firms or pharmaceutical firms. Most of these observations are chemicals companies, although some are involved in processed food products, others are involved in agricultural biotechnology applications, and a few are primarily classified as 'holding companies'.

While biotechnology firms have 56 patents at the mean and 22 patents at the median, their non-biotechnology partners have 1755 patents on average. The largest partner, Eastman Kodak (parent company of Sterling Drug at the time of the 12 observed biotech research and development ventures), has 9977 patents in its portfolio.

The second weakness of the measure is that it suffers from a number of biases (Hall, Jaffe, and Trajtenberg, 2001). These are: 1) A truncation bias. Patents that are filed later in time will be cited by fewer patents because some of the citing patents (patents that will cite it) haven't issued yet. This would lead to a conclusion that firms did not learn through the alliance, as there would be more citations pre- than post-alliance. However, Hall, Jaffe, and Trajtenberg also find that the truncation bias has diminished over time, as the pace of innovation has quickened. 2) A bias from increased citation propensity over time. (Recently issued patents cite more patents as prior art than older patents do). This would lead to fewer citations pre- than post-alliance, and a spurious finding that firms learned through the alliance. The implication of the work by Hall, Jaffe, and Trajtenberg is that these problems collectively would bias the results toward finding that partners cite each other more post-alliance.

deflators reported by Hall, Jaffe, and Trajtenberg (2001).

3.2 Proximity

An alternative method of measuring knowledge flows looks at the overlap in firm technology trajectories. This measure was first implemented by Jaffe (1989). It calculates the closeness of firms in technology space using patent classes as opposed to patent citations. Patent classes are technological fields assigned to each patent when it is awarded by the patent examiner. The patents are assigned a 3-digit primary class, a 3-digit subclass, and some-

times a sub-subclass according to the technology involved. Jaffe's measure looks at how a firm's patents are distributed across these classes, treating each class as a distinct technology space, and how that distribution compares to its partner's patent class distribution. The measure, known as the angular separation of vectors, estimates the cosine of the angle between firm i's and firm j's technology vectors (f), where each vector element contains the count of patents assigned to each specific patent class. This measure, which Jaffe calls the "technological proximity" measure is:

$$\text{Technological Proximity}_{Jaffe} = \frac{\sum_{k=1}^{K} f_{ik} f_{jk}}{(\sum_{k=1}^{K} f_{ik}^2)^{1/2} (\sum_{k=1}^{K} f_{jk}^2)^{1/2}} \tag{2}$$

In this case as well, the central measure of interest is the change in the technological proximity measure pre- vs. post-alliance.

While disparity in raw counts of patents may limit the usefulness of the cross-citation measure, there are some limitations to the technological proximity measure, as well. First, because it measures the angle between firm technology trajectories, it captures whether the firms jointly move together or apart, rather than unidirectional knowledge flows from one firm to another. It therefore acts as a complement to, rather than a substitute for the cross-citation measure. Second, the technology proximity measure is not direct evidence of firm-to-firm learning. Citations indicate know-how from a specific firm (perhaps the alliance partner) as the source of the prior art innovation. In contrast, the proximity measure reveals the degree of correlation in technological fields between two firms. Firms may move closer together in technology space independently of learning through an alliance. Lastly, the results are sensitive to the order of aggregation at the patent class level. If firms move into new fields at different rates, one is more likely to find that firms diverge in technology space if one calculates this measure

at the 6+ digit level of patent class (class plus subclass plus sub-subclass), than at the 3-digit (primary patent class) level.

4 Data

The alliance data used in this study comes from the 1987 (vol. 1); February, 1988 (vol. 1, sup. 5); April, 1991 (vol. 5); April, 1993 (vol. 7); and April, 1995 editions of Bioscan. Bioscan tracks all firms involved in biotechnology R&D through surveys and press reports. Although the volumes are retrospective, it is necessary to collect information from multiple years to construct a complete panel because Bioscan drops observations over time. This paper examines all R&D alliances formed by U.S. publicly traded firms reported in Bioscan that had an initial public offering by 1991. The data contains all alliance partnerships, including partnerships with foreign firms. There are 238 R&D alliances and joint ventures reported for these firms. This information was verified wherever possible through extensive searches using Nexis/Lexis.

To construct the patent portfolios of the above biotechnology firms and their partners, I collected information on firm subsidiaries and merger-acquisition activity. In total, the data contains the patent portfolios for 91 biotechnology firms, and 79 partners. I extracted patents for all firms and their subsidiaries for a base year, 1991. I obtained subsidiary information through two sources: *The Directory of Corporate Affiliations* (otherwise known as *Who Owns Whom*), and *Moody's Manuals.* Using the history information given in Moody's as well as historical firm information from *Hoover's Company Profiles*, I additionally collected the patents of acquisition targets prior to 1991, whose names do not appear in the subsidiary lists. I updated these lists by adding the patent portfolios for significant acquisitions, for the 1991-1996 time period, using *Moody's Manuals*, *Nexis/Lexis*, *Edgar*,

and *Hoovers Company Profiles.* I also accounted for name changes (typically as the result of a merger). Using these sources resulted in a base list of 2,357 firm and subsidiary names.

The patent data comes from the U.S. Patent and Trademark Office (USPTO) Micropatent database. The data contains granted patents with application dates between 1980-1996. Because the biotechnology industry is a nascent industry, few firms were in operation before 1980. As a result, I restrict patent portfolios for each alliance to begin in the year the biotechnology firm was founded, or 1980, whichever is the later event.

Patent data was extracted from the Micropatent database using substring searches, and then deleting records that were not correct based on names, states and countries. Substring searches were necessary to ensure the collection of patents for all variants of the firm names. For example, Perkin-Elmer Corp. appears in 27 different name variations. Using this methodology, there were 5,382 permutations of firm names and subsidiaries, as they appeared in micropatent. The total data collection resulted in 134,654 patents, which in turn contained 929,613 patent citations.

Patent data panels at the firm level are very difficult to construct due to changes in firm structure through merger and acquisition, as well as the presence or creation of subsidiaries. Previous authors have assumed a constant corporate structure over time. Because of the significant merger and acquisition activity in the biotechnology and pharmaceutical industries during recent years, I collected patent data to accommodate M&A activity. This was in part necessary because several of the pharmaceutical alliance partners engaged in major mergers over the relevant time period.

The ideal patent portfolio for a changing company is difficult to envision. Major mergers and acquisitions may result in substantial changes in the research trajectory of the firm. In theory, perhaps patents from merged

entities should only be included in the patent portfolio on or after the merger date, since this might represent the true technological position of the firm. In practice, however, exclusion of acquired company patents can distort the interpretation of the alliance effect for either or both of the pre-alliance overlap and post-alliance overlap measures. First, if a major merger caused a shift in the technological trajectory of the combined firm post-alliance, the researcher might be tempted to conclude that the convergence or divergence of the research paths of the alliance partners is attributable to the alliance, when in fact it would be an artifact of the merger. As a result, I include the patent portfolio of the acquired or merged entities pre-merger. While this measure incorrectly states the *level* of technology overlap, it will not bias the *change* in technological trajectories from the alliance.

5 Results

The empirical results are summarized in tables 4 - 10. The overall pattern suggests that while convergence in technology space is the norm for biotech alliance partners, this convergence is *not* attributable to the alliances themselves. Rather, the convergence is due to widespread movements by the industry into new technological fields.

Table 4 shows the cross-citation rates per alliance for joint ventures, research alliances, and development alliances. In general, very few firms cited their partners *at all*. Of 23 joint ventures, one joint venture partner cited the other in only 6 cases. Of 96 research alliances, 21 had cross-citations, and of 106 development alliances, 17 had cross-citations. This result is surprising in that the cross-citation rates are in some senses *liberal* measures: they count cases where one firm cites any of its partner's patents rather than looking for citations to a patent that specifically resulted from alliance-related research. What is more surprising, however, is the utter failure of phar-

maceutical and chemical firms to cite their biotechnology partners. Of all 238 alliances, there were no cases where a pharmaceutical (or agrochemical) firm cited its biotechnology partner. The failure of alliance partners to cite each other is not because biotechnology innovation is non-sequential. In fact, the 3437 biotechnology patents of firms in R&D alliances were cited by 17,346 subsequent patents. While firms do cite each other in the industry, alliance partners during this period evidently do not. This result is completely at odds with the hypothesis that pharmaceutical firms have allied with biotechnology firms to access new technology. It is also at odds with the hypothesis that both firms enter an alliance for mutual knowledge sharing. These results leave room for the hypothesis that firms specialize in alliances.

While the cross-citation rate methodology suggests little to no transfer of knowledge between alliance partners in this industry, it may be an overly *narrow* measure. Alliance partners may gain new knowledge through the alliance in areas that are more broad than the specific purpose of the alliance, or perhaps more distantly related to the technology than would necessitate the direct citation of a partner's patent. The cross-citation methodology is unable to capture more broad movements in knowledge flows. To examine this issue further, I employ the Jaffe technological proximity measure explained above.

Tables 5 lists the pre- and post-alliance trajectory overlap using the proximity measure, as well as the gain or loss in overlap (post-alliance trajectory - pre-alliance trajectory) at the primary (3-digit) patent class level. For each type of alliance: joint venture, research alliance, and development alliance, firms converged in technology space post-alliance *on average*, but roughly one-forth of the alliances showed divergence in technology space. Moreover, the pre-alliance level of overlap varies strikingly across alliance pairs. This illustrates the varied nature of alliance partners in biotechnology alliances. The variability in the proximity measure: ranges from 0 for the Diagnostic

Products Corp - Dainippon Ink and Chemicals joint venture, to .99 in the case of a PolyCell and Chiron research alliance.

To further explain this variation, Table 6 partitions the data into biotechnology-biotechnology alliances, biotechnology - pharmaceutical alliances (pharmaceuticals are defined as firms with a primary SIC of 2834 or 2835)[5], and biotechnology - non-biopharma alliances. Unfortunately, many of the biotechnology-biotechnology alliance observations were dropped because at least one of the two firms had no patents pre- or post-alliance. (This is an important limitation to the use of patent statistics as indicators for new industries). Table 6 shows that when biotechnology firms pair with other biotechnology firms, they have higher levels of technological overlap both pre-and post alliance than when they pair with other firms. In contrast, biotechnology - non-biotechnology alliances have a relatively low overlap of technological fields, with a mean overlap from 0.2 - 0.3.[6] These partner firms are significantly larger than their biotechnology partners, and have more diverse operations. Table 2 details the major business fields by firm, as described in *Moody's Manuals*.

After correcting for partner type, the limited evidence of biotech - biotech joint ventures suggests that they converged in technology space most. In addition, technology convergence of biotech - pharmaceutical alliance partners was not statistically different from that of biotech - non-biopharma partners.

Next, I explore whether the proximity measures are understating know-how exchange in biotechnologies because they measure the movement of firms in all technology fields, rather than in just biotechnology. Many of the partner firms are engaged in a wide variety of business units and patent in a wide variety of patent classes. It is possible, however, that even large con-

[5]Standard Industrial Classification code 2834 is the code for "pharmaceutical preparations", and SIC 2835 represents "in vitro and in vivo diagnostics".

[6]The pre-alliance overlap measures between biotech - pharma alliances and biotech - non-biopharma alliances are not statistically significantly different.

glomerates have small specialized units that are actively engaged in biotechnology research and actively learning through their alliance partners.

In order to better test whether conglomerates are absorbing biotechnology knowledge flows, I restrict the patent portfolios to examine only patents in biotech-related 3 digit classes.[7] To do this, I restrict the measure to count only three digit classes in which biotechnology firms in the sample have been granted patents. Tables 7 - 9 compare the technology proximity measure by type of alliance: joint venture, research, and development; by type of partner firm: pharmaceutical, biotechnology, and non-biopharma; and by level of patent class aggregation: all 3-digit patent classes, biotechnology 3- digit patent classes, and biotechnology 5-digit patent classes (this is the primary 3-digit class plus the first two digits of the patent subclass).

The results show that even looking *within* biotechnology fields, however, pharmaceutical and non-biopharma conglomerates with specialized biotechnology units are not patenting in the same areas as their biotechnology partners. The average overlap remains around 20% for biotechnology-pharmaceutical, and biotechnology - non-biopharma alliances.[8] Moreover, restricting focus to only the biotechnology patents does not strengthen the rate of convergence in technologies. This suggests that even focusing only on the biotechnology field, alliance partners co-specialize.

Finally, I explore the question of whether the average convergence of firms in technology space is attributable to the participation in alliances, or simply due to general movement of the industry as a whole into the same technological direction. To do this, I conduct a match-pair analysis, where I

[7]Pharmaceutical partners have roughly 40% of their patents in these technology classes.

[8]The sensitivity of the technology proximity measure to the level of disaggregation in patent class (3 vs. 5 digits) is to be expected. The technological proximity measure divides the patent portfolio into bins, one for each patent class or subclass unit. These firms are collectively involved in 429 primary patent classes, 101 biotechnology 3-digit patent classes, and 3,128 biotechnology 5-digit patent classes. As a result, it is expected that the raw level of overlap should decrease when going from 3- to 5-digit classes.

randomly assign each biotechnology firm to a partner from within the list of existing partners. Table 10 shows the results of this analysis at both the all 3-digit patent class level, and the biotechnology 5-digit patent class level.

The results indicate that the convergence in technology proximity measures attributable to participation in alliances is not statistically different from that for the random match pairs. In other words, the results suggest that while firms are converging in technology space over time, this is a general phenomenon of the industry, and not a result of the alliance. This analysis confirms the cross-citation analysis results: biotechnology alliances are *not* resulting in increased knowledge accumulation across firms. These findings are consistent with the hypothesis that firms specialize in alliances, and refute the hypotheses that alliances result in increased learning - at least in core technology areas - by one or both partners.

6 Conclusion

Do firms utilize alliances to learn the core technologies of their partners? This paper finds that in the early biotechnology industry the answer is "no". I use data on 238 biotechnology R&D strategic alliances and joint ventures from 1985-1991, as well as the patent portfolios of 168 biotechnology firms and their partners from 1980-1996. I fail to find evidence consistent with the hypothesis of knowledge flow across alliances: neither from biotechnology firm to its partner, nor from partner to the biotechnology firm. This phenomenon holds true controlling for partner type.

While the two methods utilized in this paper: one using patent citations, and one using patent classes, have given consistent results, an alternative explanation is that patent data is not accurately capturing knowledge flows. Yet, patent data likely offers the best measure of technology flow. In addi-

tion, these results confirm prior case-based research in the industry.

What remains to be understood is how firms in these industries have learned new skills and innovated. The biotechnology industry represents a newly emergent field that is very innovative. In addition, it is generally recognized that the incumbent pharmaceutical industry has adapted to the biotechnology revolution, so the question remains: how? Other scholars have noted the role of university-firm interaction, as well as the importance for in-house scientists to coauthor papers with external scientists. In addition, scholars of the geographic localization of knowledge spillovers note the possible role of labor turnover in innovation. Future research in the management of innovation should pursue this line of inquiry.

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Table 1: Value of Alliances Relative to Firm Finance Offerings
($s in Millions)
(96 firms)

Source of Revenue	# Obs.	Mean	Min	Max
Debt	6	$63.0	$10.0	$125
Initial Public Offering	82	$22.0	$1.7	$107
Follow-on: Preferred Stock	4	$31.2	$15	$60
Follow-on: Common Stock	45	$32.0	$0.7	$115
Warrants	2	$8.8	$6.6	$11
Research Alliance	52	$17.0	$0.8	$220
Development Alliance	23	$24.1	$0.5	$210
Production Alliance	2	$9.6	$1.2	$18
Grants	56	$0.7	$0.05	$10

*ALZA excluded for two debt issues of $750, and $825 Million.
Source: Bioscan and SDC.

Table 2: Partner Firm Patents (1980-1996) And Firm Activities

Partner Firm	Patent Count	Principal Business
Eastman Kodak	9977	Dvlp., Mfgr., Mktg.; Imaging; Information Systems; Chemicals; Health Products
Bayer AG	9829	Photochemicals; Prodctn. and Mktg. of Chemicals, Pharmaceuticals; Imaging
Dow	8439	Chemicals; Plastics; Consumer Products (including Ethical Pharmaceuticals); Herbicides; Consumer Products; Energy
Du Pont	8193	Chemicals; Fibers; Polymers; Petroleum
Hoechst	7784	Mfgr. Pharmaceuticals; Plastics; Chemicals; Fibers; Herbicides; Fine Chemicals; Plant Engineering
Ciba-Geigy AG	5870	Prodctn. and Mktg.: Dyestuffs and Chemicals; Pharmaceuticals; Agricultural Products; Plastics; Instruments
Royal Dutch	3934	Petroleum; Energy
Phillips Petroleum Co.	3415	Petroleum Exploration; Chemical Prodctn. and Distrib.
Monsanto	2891	Mfgr. and Mktg. Agricultural Products; Chemicals; Pharmaceuticals; Food Products
Merck & Co.	2858	Drug Discovery and Dvlp.; Human; Veterinary; Specialty Chemicals
Proctor & Gamble	2764	Detergents; Personal Care Products; Food Products; Ethical Drugs
Eli Lilly	2444	Drug Discovery, Dvlp., Mfgr., Distrib.; Including Ethical Drugs, Medical Devices; Diagnostic Products; Veterinary
American Cyanamid	2378	Pharmaceutical Products (Vaccines, Nicotine Patch); Devices; Herbicides; Chemicals
Johnson & Johnson	2350	Mfgr. and Mktg.; Consumer Products; Ethical Pharmaceuticals
Rhone Poulenc Rorer S.A.	2342	R&D; Prodctn.; Mktg.; Intermediate Organic and Inorganic Chemicals; Pharmaceuticals; Specialty Chemicals; Fibers
Sumitomo Chemical Co., Lt	2214	Mfgr. Herbicides; Dyestuffs; Bulk Pharmaceuticals; Agricultural Chemicals; Resins; Rubber
Akzo N.V.	2111	Fibers and Polymers;Salt and Basic Chemicals Prodctn.; Coatings; Ethical Drugs; Hospital Supplies; Diagnostics; Pharm. Raw Materials
Hoffmann-La Roche Inc.	1816	Pharmaceuticals; Diagnostics; Vitamins; Fine Chemicals; Perfumes; Flavorings; Plant Protection
American Home Products	1815	Mfgr. and Mktg.; Healthcare Products, Food Products

Table 2: (continued)

Partner Firm	Patent Count	Principal Business
Pfizer	1810	Ethical Pharmaceuticals; Drug Discovery and Dvlp.; Devices; Consumer Products; Specialty Chemicals
Philip Morris	1722	Tobacco; Food Products
Bristol-Myers Squibb	1621	Drugs; Medical Devices; Consumer Products; Toiletries; Household Products
W. R. Grace & Co.	1620	Specialty Chemicals; Health Care (Dialysis and Respiratory Therapy) Services and Products; Agricultural; Petroleum; Equipment
Abbott	1567	Discovery, Dvlp., Mfgr., Mktg.; Pharma. and Nutritional Products; Hospital and Laboratory Products
Warner-Lambert Co	1499	R&D; Mfgr.; Mktg.; Ethical Pharmaceuticals; Biologicals; Specialty Chemicals; Consumer Products
R. J. Reynolds	1302	Tobacco; Food Products
SmithKline Beecham Corporation	1291	R&D, Discovery, Mfgr., Mktg.; Ethical Pharmaceuticals; Laboratory Testing
Baxter International Inc.	1258	Dvlp., Mfgr., Distrib.; Hospital Products, Medical Systems; (Lab equipment; Blood Dialysis)
Takeda Chemical Industries,	1248	Prodctn.; Mktg.; Pharmaceuticals; Vitamins; Chemicals; Food Products; Herbicides
Roussel-Ulcaf	1236	Mfgr.; Mktg.; Ethical Pharmaceuticals; Chemicals; Cosmetics
Upjohn	1224	R&D, Prodctn.; Mktg. Ethical Pharmaceuticals; R&D Prodctn. Agricultural Products (Seeds)
Sandoz	1184	R&D; Mfgr.; Ethical Drugs; Pharmaceuticals; Related Chemicals
Nippon Steel	1183	Steel; Engineering and Construction; Electronics and Information; Biotechnology
Colgate-Palmolive	1144	Develop. Distrib. Mfgr.; Household, Pet Care, and Personal Care Products
Becton Dickinson	922	Medical Supplies, Devices, Diagnostic Systems
Boehringer Manheim GmbH	859	Mfgr. Pharmaceuticals; Diagnostic Instruments; Medicinal Chemicals; Consumer Products; Chemicals
Schering A.G.	770	Chemical and Pharmaceutical Prodctn.; Herbicides; Equipment; Chemicals
Merck AG	746	R&D, Mfgr., Distrib.; Pharmaceuticals and Chemicals
Schering Inc.	727	R&D, Discover, Mfgr., Mktg.; Ethical Pharmaceuticals; Health Care Products
Perkin-Elmer Corp.	635	Instruments (Polymerase Chain Reaction); Material Sciences (Plasma Thermal) Equipment

Table 2: (continued)

Partner Firm	Patent Count	Principal Business
International Minerals & Chemical Corp	588	Medical Instruments; Radiology; Cardiology; Nuclear Medicine; Anesthesiology Instruments
Dainippon Ink & Chemicals	564	Prodctn. and Mktg.; Chemicals, Imaging; Coatings; Biochemicals; Petrochemicals; Machinery
Uniroyal	556	Chemicals
Glaxo	489	Mfgr. and Distrib. Pharmaceutical Preparations; Ethical Drugs; Vitamins; Vaccines; Food; Veterinary
Ajinomoto Co, Inc.	484	Mfgr. Food Products and Life-Science Products (Pharmaceuticals, Amino Acids, Specialty Chemicals)
Lubrizol Enterprises, Inc.	483	Specialty Chemicals; Agribusiness
Burroughs Wellcome	478	R&D, Mfgr.; Mktg.; Ethical Pharmaceuticals; Diagnostic Reagents; Pesticides
Enichem Spa	474	Prodctn. and Sale Chemical Products
Boehringer Ingeleheim GmbH	405	Mfgr. and Distrib. of Pharmaceuticals; Herbicides;
Farmatalia Carlo Erba	401	Mfgr. and Distrib. Pharmaceuticals; Chemicals; Veterinary; Ethical Drugs; Reagents; Laboratory Materials
Nippon Zeon Co., Ltd.	394	Prodctn. and Distrib.; Synthetic Rubbers; Plastics; Chemicals; Medical Products
Yamanouchi	384	R&D, Mfgr; Ethical Pharmaceuticals
Eisai Co., Ltd.	369	Mktg.; Ethical Drugs; Cosmetics; OTC Drugs; Toiletries; Medical Instruments; Fine Chemicals; Food Products; Machinery
S. C. Johnson & Son	359	Mfgr. Soaps; Wax Products; Insecticides; Personal Care Products
AB Astra	281	Mfgr., Distrib., and Mktg.; Pharm. Products, and Medical Care Equipment (Infectious Diseases, Central Nervous System)
Pharmacia AB	269	Mfgr. Pharmaceuticals; Biotechnology; Tobacco; Processed Foods; Beverages
Daiichi Pharmaceutical	265	R&D, Manufact., Mktg.; Ethical Pharmaceuticals; Food Additives; Feed Supplements
Tanabe Seiyaku Co	232	R&D; Ethical Pharmaceuticals;
Chugai	226	Ethical Pharmaceuticals; Personal Health Care Products; Diagnostic Products; Agrochemicals
Suntory Limited	213	Alcohol Prodctn.; Beverages
Kirin	144	Alcohol Prodctn.; Restaurants; Beer; Beverage Distrib.; Life Sciences
Quantum Chemical Corporation	125	Mfgr.; Resins; Petrochemicals

Table 2: (continued)

Partner Firm	Patent Count	Principal Business
Taisho Pharmaceutical	115	Mfgr.; Mktg.; Drugs; Toiletries; Consumer Products; Herbicides; Investment and Funding R&D
Campbell Soup Co.	89	Mfgr. and Preparation of Convenience Foods
Petrofina	81	Exploration and Prodctn.; Petroleum; Petrochemicals
Altana Industrie-Aktien	72	Mfgr. Pharmaceuticals; Mfgr. Cereals
Hafslund Nycomed A/S	70	Medical Imaging; Diagnostics; Pharmaceuticals; Hospital Equipment
Mean	1755	
Median	1144	
Quartile 1	398	
Quartile 2	1144	
Quartile 3	1964	
Quartile4	9977	

Table 3: Partner Firm Patents: 1980-1996

Biotech Firm	Patent Count
Chiron	638
ALZA	551
Genentech,	286
Scios Nova	144
Mycogen Plant Sciences, Inc.	127
The Liposome Company, Inc.	126
Genetics Institute, Inc.	113
AMGEN	91
Immunex	87
NeoRx Corporation	77
Genex Corp.	73
Centocor	70
Sepracor	66
Biogen Inc.	63
Calgene Chemical, Inc.	62
Enzon Corp.	60
ICN Pharmaceuticals	59
GEnzyme (U.K.) Ltd.	49
DNA Plant Technology	48
ISIS Pharmaceuticals	46
Repligen	46
Environmental Diagnostics	44
Nova Pharmaceutical Corporation	44
MGI Pharma, Inc.	40
BIO-Technology General Corp.	38
Liposome Technology Incorporated	38
Cygnus Corporation	32
Alliance Pharmaceutical Corp.	30
Genome Therapeutics	30
Glycomed Incorporated	28
Immunomedics	25
Cellcor Corporation of Canada Limited	23
Genelabs Incorporated	23
Synergen Associates, Inc.	22

Table 3: (continued)

Biotech Firm	Patent Count
Enzo Biochem, Inc.	21
Molecular Biosystems, Inc.	21
RIBI Immunochem Research, Inc.	21
Alkermes	19
Alteon Inc.	18
Epitope	18
Advanced Tissue Sciences, Inc.	17
Neogen	17
Biomatrix, Inc,	16
Celtrix Laboratories, Inc.	16
ProCyte Corporation	16
Atrix Laboratories, Inc.	15
Ecogen Inc.	14
Synbiotics Corporation	14
Embrex Inc.	13
Oncor	13
Regeneron Pharmaceuticals	13
T Cell Sciences, Inc.	13
BioTechnica International, Inc.	12
Cephalon, Inc.	12
Escagenetics Corporation	12
Oncogene Science	12
Cambridge Bioscience	11
Applied Immune Sciences, Inc.	10
COR Therapeutics, Inc.	9
Interneuron Pharmaceuticals Inc.	9
Somatix Therapy	8
Syntro Corporation	8
Ventrex Laboratories	8
Agouron Pharmaceuticals, Inc.	7
Athena Neurosciences, Inc.	7
Cambridge Biotech Corporation	7
Deprenyl Animal Health, Inc.	7
Anergen, Inc.	6

Table 3: (continued)

Biotech Firm	Patent Count
Crop Genetics International	6
ICOS Corporation	6
Lidak Pharmaceuticals	6
Magainin Pharmaceuticals Inc.	6
Vertex Pharmaceuticals Incorporated	6
American Bionetics, Inc.	5
Aphton Corp.	5
CellPro Incorporated	5
Cytel Corporation	5
Lifecore Biomedical, Inc.	5
Somatogen, Inc.	5
Cambridge NeuroScience, Inc.	4
Diagnostic Products	4
ImClone Systems Incorporated	4
Immulogic Pharmaceutical Corp.	4
Dianon Systems, Inc.	3
Cellular Products, Inc.	2
Genetic Therapy, Inc.	2
Unigene Laboratories, Inc.	2
Cistron Biotechnology, Inc.	1
JBL Scientific, Inc.	1
MedImmune, Inc.	1
Mean	56
Median	22
Quartile 1	13
Quartile 2	22
Quartile 3	54
Quartile4	638

Table 4: Cross-Citation Rates

Joint Ventures

	Biotechnology Firm (Citations to Partner Patents)	Partner (Citations to Biotechnology Patents)
# Obs. With Zero Patents Pre- or Post- Alliance	6	1
# Obs. With Zero Cross-Citation Rates	11	22
# Obs. Citing Alliance Partner	6	0
Avg. Change in Cross-Citation (Post-Pre Alliance)	-0.0042	NA

Research Alliances

	Biotechnology Firm (Citations to Partner Patents)	Partner (Citations to Biotechnology Patents)
# Obs. With Zero Patents Pre- or Post- Alliance	29	2
# Obs. With Zero Cross-Citation Rates	46	94
# Obs. Citing Alliance Partner	21	0
Avg. Change in Cross-Citation (Post-Pre Alliance)	0.0008	NA

Development Alliances

	Biotechnology Firm (Citations to Partner Patents)	Partner (Citations to Biotechnology Patents)
# Obs. With Zero Patents Pre- or Post- Alliance	33	5
# Obs. With Zero Cross-Citation Rates	56	101
# Obs. Citing Alliance Partner	17	0
Avg. Change in Cross-Citation (Post-Pre Alliance)	0.0007	NA

Table 5: Technology Trajectory Changes As Knowledge Flows

Joint Venture Knowledge Flows
Calculated For All 3-Digit (Primary) Patent Classes

	Pre-Alliance Overlap	Post-Alliance Overlap	Difference Overlap
Mean	0.2442	0.3152	0.0710
Median	0.1561	0.2772	0.0348
Q1	0.0922	0.0992	-0.0095
Q2	0.1561	0.2772	0.0348
Q3	0.3582	0.5109	0.1716
Q4	0.6847	0.8455	0.4513
18 Observations			

Research Alliance Knowledge Flows
Calculated For All 3-Digit (Primary) Patent Classes

	Pre-Alliance Overlap	Post-Alliance Overlap	Difference Overlap
Mean	0.2289	0.2792	0.0503
Median	0.1242	0.1491	0.0186
Q1	0.0639	0.0713	-0.0153
Q2	0.1242	0.1491	0.0186
Q3	0.2781	0.4153	0.1017
Q4	0.9971	0.9963	0.6080
71 Observations			

Development Alliance Knowledge Flows
Calculated For All 3-Digit (Primary) Patent Classes

	Pre-Alliance Overlap	Post-Alliance Overlap	Difference Overlap
Mean	0.2665	0.3611	0.0946
Median	0.1884	0.2449	0.0437
Q1	0.0932	0.1360	-0.0034
Q2	0.1884	0.2449	0.0437
Q3	0.3881	0.6124	0.1575
Q4	0.9497	0.9699	0.6838
76 Observations			

Table 6: Knowledge Flows Segmented By Partner Type

Joint Venture Knowledge Flows
Calculated For All 3-Digit (Primary) Patent Classes

Partner Type	Statistic	Number of Observations	Pre-Alliance Overlap	Post-Alliance Overlap	Difference Overlap
Pharmaceutical	Mean	8	0.2999	0.4292	0.1293
	Stdev		0.2252	0.2088	0.2619
Non-Biopharma	Mean	9	0.1986	0.2131	0.0146
	Stdev		0.2187	0.2935	0.1553
Biotech		1	0.2104	0.3226	0.1122

Research Alliance Knowledge Flows
Calculated For All 3-Digit (Primary) Patent Classes

Partner Type	Statistic	Number of Observations	Pre-Alliance Overlap	Post-Alliance Overlap	Difference Overlap
Pharmaceutical	Mean	30	0.2422	0.3455	0.1033
	Stdev		0.2296	0.2599	0.2309
Non-Biopharma	Mean	37	0.1692	0.1785	0.0093
	Stdev		0.1871	0.2384	0.1662
Biotech	Mean	4	0.6824	0.7141	0.0317
	Stdev		0.4713	0.4799	0.0658

Development Alliance Knowledge Flows
Calculated For All 3-Digit (Primary) Patent Classes

Partner Type	Statistic	Number of Observations	Pre-Alliance Overlap	Post-Alliance Overlap	Difference Overlap
Pharmaceutical	Mean	30	0.2012	0.3203	0.1191
	Stdev		0.1595	0.2194	0.1749
Non-Biopharma	Mean	36	0.2748	0.3234	0.0486
	Stdev		0.2355	0.2942	0.2288
Biotech	Mean	10	0.4355	0.5895	0.1539
	Stdev		0.2492	0.3590	0.2882

Pharmaceutical - partner firm with primary SIC classification 2834 or 2835
Other - partner firm that is neither a dedicated biotechnology firm nor has a primary SIC classification of 2834-2835

Table 7: Joint Venture Technology Trajectories - Alternative Measures

			All 3-Digit Classes Calculated at 3-Digit		Biotech 3-Digit Classes Calculated at 3-Digit		Biotech 3-Digit Classes Calculated at 5-Digit	
Partner Type	Number of Observations	Statistic	Pre-Alliance Overlap	Difference Overlap	Pre-Alliance Overlap	Difference Overlap	Pre-Alliance Overlap	Difference Overlap
Pharmaceutical	8	Mean	0.2999	0.1293	0.3048	0.1335	0.0709	0.0822
		Stdev	0.2252	0.2619	0.2295	0.2629	0.0578	0.1148
Chemical	9	Mean	0.1986	0.0146	0.2390	0.0109	0.0487	0.0366
		Stdev	0.2187	0.1553	0.2177	0.1649	0.0375	0.0826
Biotech	1		0.2104	0.1122	0.2104	0.1122	0.0523	0.1148

Pharmaceutical - partner firm with primary SIC classification 2834 or 2835
Other - partner firm that is neither a dedicated biotechnology firm nor has a primary SIC classification of 2834-2835

Table 8: Research Alliance Technology Trajectories - Alternative Measures

			All 3-Digit Classes Calculated at 3-Digit		Biotech 3-Digit Classes Calculated at 3-Digit		Biotech 3-Digit Classes Calculated at 5-Digit	
Partner Type	Number of Observations	Statistic	Pre-Alliance Overlap	Difference Overlap	Pre-Alliance Overlap	Difference Overlap	Pre-Alliance Overlap	Difference Overlap
Pharmaceutical	30	Mean	0.2422	0.1033	0.2370	0.1317	0.0690	0.0281
		Stdev	0.2296	0.2309	0.2301	0.2403	0.0653	0.0629
Chemical	37	Mean	0.1731	0.0093	0.1971	0.0014	0.0506	0.0182
		Stdev	0.1871	0.1662	0.1890	0.1663	0.0938	0.0910
Biotech	4	Mean	0.6824	0.0317	0.7350	0.0597	0.5505	0.0318
		Stdev	0.4714	0.0658	0.3707	0.0715	0.5139	0.0824

Pharmaceutical - partner firm with primary SIC classification 2834 or 2835
Other - partner firm that is neither a dedicated biotechnology firm nor has a primary SIC classification of 2834-2835

Table 9: Development Alliance Technology Trajectories - Alternative Measures

			All 3-Digit Classes Calculated at 3-Digit		Biotech 3-Digit Classes Calculated at 3-Digit		Biotech 3-Digit Classes Calculated at 5-Digit	
Partner Type	Number of Observations	Statistic	Pre-Alliance Overlap	Difference Overlap	Pre-Alliance Overlap	Difference Overlap	Pre-Alliance Overlap	Difference Overlap
Pharmaceutical	30	Mean	0.2012	0.1191	0.2446	0.1474	0.0496	0.0480
		Stdev	0.1595	0.1749	0.1951	0.1994	0.0594	0.0563
Chemical	36	Mean	0.2748	0.0486	0.2605	0.0456	0.0837	0.0042
		Stdev	0.2355	0.2288	0.2301	0.2201	0.1591	0.0929
Biotech	10	Mean	0.4355	0.1539	0.4360	0.1535	0.1023	0.0361
		Stdev	0.2492	0.2882	0.2487	0.2883	0.2423	0.1438

Pharmaceutical - partner firm with primary SIC classification 2834 or 2835
Other - partner firm that is neither a dedicated biotechnology firm nor has a primary SIC classification of 2834-2835

Table 10: Random Match Pair Analysis

Joint Venture Random Match Pair Analysis
All 3-Digit Classes (Calculated at 3-Digit Level)

Partner Type	Number of Observations	Statistic	Pre-Alliance Trajectory	Difference Trajectory
Pharmaceutical	8	Mean	0.2999	0.1293
		Stdev	0.2252	0.2619
Chemical	9	Mean	0.1986	0.0146
		Stdev	0.2187	0.1553
Biotech	1		0.2104	0.1122
Random Assignment	19	Mean	0.1911	0.0877
		Stdev	0.2037	0.2077

Research Alliance Random Match Pair Analysis
All 3-Digit Classes (Calculated at 3-Digit Level)

Partner Type	Number of Observations	Statistic	Pre-Alliance Trajectory	Difference Trajectory
Pharmaceutical	30	Mean	0.2422	0.1033
		Stdev	0.2296	0.2309
Chemical	37	Mean	0.1731	0.0093
		Stdev	0.1871	0.1662
Biotech	4	Mean	0.6824	0.0317
		Stdev	0.4714	0.0658
Random Assignment	66	Mean	0.1870	0.0319
		Stdev	0.2185	0.2056

Development Alliance Random Match Pair Analysis
All 3-Digit Classes (Calculated at 3-Digit Level)

Partner Type	Number of Observations	Statistic	Pre-Alliance Trajectory	Difference Trajectory
Pharmaceutical	30	Mean	0.2012	0.1191
		Stdev	0.1595	0.1749
Chemical	36	Mean	0.2748	0.0486
		Stdev	0.2355	0.2288
Biotech	10	Mean	0.4355	0.1539
		Stdev	0.2492	0.2882
Random Assignment	74	Mean	0.2186	0.0751
		Stdev	0.2037	0.2077

Pharmaceutical - partner firm with primary SIC classification 2834 or 2835
Other - partner firm that is neither a dedicated biotechnology firm nor has a primary SIC classification of 2834-2835

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